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Memory Modelling Schemes In Neuromorphic VLSI Chips Using Reinforcement Learning Based on Cognition A Computational Cognititve Neuroscience Approach

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Abstract

Software Technology is ever evolving, the pressure on hardware Industry for incorporating more ICs in a single chip is increasing. Scaling in VLSI Chips is finding its limitations due to secondary effects. Moreover the demand to be intelligent is posing new challenges to Chip manufacturers. The only way to mimic human intelligence in machines is to build the architecture of these machines based on our nervous system. Neuromorphic Engineering appreciates various concepts of biology and allows a designer to incorporate ICs based on bio-inspired architectures. This work focuses on implementation of reinforcement learning based on Computational Cognitive Neuroscience in Neuromorphic VLSI Chips. Attention is modelled based on BDI. Selective attention is done and only necessary data is sent to memory using Reinforcement learning. Memory optimization is achieved by only extracting the abstracts and storing them into short term memory, working memory and long term memory.

Keywords: computational cognitive neuroscience, neuromorphic engineering, reinforcement learning.

Introduction

The need of intelligence is driving the current industry. All organizations are investing a large amount of time and manpower in producing intelligent products. Smart devices have made us very comfortable and reduced redundancy in operations. We are in pursuit of intelligence now.

All controls and automation happens through a processor or a set of processors (in digital domain). These computing devices are made up of several ICs. Till 1980s the ICs industry was working with a motto of "small is beautiful" i.e. miniaturization, which was accomplished by MOS Scaling. The next decade was of "speed is the need" i.e. fast processing which was accomplished by dual core, quad core and recently octa core which exhibited high speed parallel processing. As a result we have devices commercially available, built on nanotechnology and multi processors. But these machines do not exhibit human behaviour. In last two decades we are striving to achieve machines which can imitate human intelligence.

The main difference between machines and humans is Cognition. This cognition is integration of all human behavioursuch as attention, perception, learning, recognition, classification etc.

Hypothesis 1: machines built on high parallel processing technology are not intelligent as they don't exhibit cognition.

How to imitate human cognition? In pursuit of intelligence we started to evolve our decision making algorithms, such as machine learning, pattern classification etc., which accounts for computational intelligence. Another approach was to mimic nervous system called as neural networks were being implemented. This became mathematical computation without any psychological component. Swarm intelligence and genetic algorithms were the recent achievements in computational intelligence. This segment of Bio-inspired computing gave some promising accuracy in decisions but yet they were still algorithms that enabled machines to take more human like decisions. Still cognition is not achieved.

There was tremendous research in hardware sector too, where sensors and actuators evolved a lot. They were miniaturized such that they can be embedded. These systems made machines to change or to take some predefined decision for any change in external environment. These systems were smart but not intelligent.

Table 1: Comparison of Brain and Computer [4]

Brain	**Computer**
Built from hydrocarbons and aqueous solutions	Built from silicon and metal
Electrical and chemical signals	Electrical signals
Transmission on neural wires	Transmission on metallic wires
Neurons are basic processing unit	Transistors are basic processing unit
Neurons contains more than 95% of wiring in volume	Physical size limits wire scaling
Wetware	Software
Cognitive neuroscience is basis for computations	Computational algorithms is basis for computing.

Only Few Comparisons

The computers were designed keeping in mind that man is programmed in childhood and executes or take decisions as he grows accordingly. The architecture was designed on this concept of data accumulation, programming, storing, processing, and executing. There was no considerations for emotions, behaviour, beliefs, faiths, desires and intensions etc. these are very fundamentally required for cognition.

Brain Vs Computers

A. What do we know about brain?

To understand cognition we need to define intelligence. To understand intelligence we should understand the human computer- Brain works [4]. Human brain exhibits adaptation and learning which is not found in machines.

Hypothesis 2: system or machine is said to be intelligent if it exhibits adaptation and learning.

B. How learing and intelligence are related? (emergent)

Learning is process of accumulating data, processing it, and extracting information from it. Learning also involves unlearning. Learning can happen at any moment. Knowledge is the output of learning. Once the knowledge is applied and experienced then patterns and entities arise thereby intelligence emerges.

Table 2: Emergenct Behaviour of Intelligence

Sl. no	Expression	One word description	Examples (In computer parlance)	Comments
1	Data	Symbols	Spreadsheet entries	Raw data collected, unorganized, no significance
2	Data+ Processing = Information i.e. data with relational connection	answers to "who", "what", "where", and "when" questions	Relational database	Information is obtained from processed data or collection of data in organized manner which makes some sense and has significance
3	Information + Processing = Knowledge	answers "how" questions	Most of the applications we use (modeling, simulation, etc.) exercise some type of stored knowledge.	Information is processed to gain knowledge. Knowledge is the appropriate collection of information, such that it's intent is to be useful. Knowledge is

				a deterministic process.
4	Knowledge + application = Understanding Knowledge + Processing = Intelligence	Think and act accordingly	AI systems possess understanding in the sense that they are able to synthesize new knowledge from previously stored information and knowledge.	Understanding is an interpolative and probabilistic process. It is cognitive and analytical. It is the process by which I can take knowledge and synthesize new knowledge from the previously held knowledge.
6	Knowledge + experience = wisdom	It asks questions to which there is no answer, and in some cases, to which there can be no humanly-known answer.	Wisdom is a uniquely human state. Till today machines are not capable of attaining it.	Wisdom is an extrapolative and non-deterministic, non-probabilistic process. Wisdom is something by virtue of which we can decide between right or wrong, good and bad.

The very basic understanding of data collection, storage, processing, representation, knowledge base, and execution in human brain will give us insights into human intelligence [5]. The best way to understand human brain is to simulate one. This might look impossible but we cannot deny that it is within our grasp.

Hypothesis-3: If we reduce the differences of information representation, transmission, storage and processing between computers and humans then we can realize intelligent machines.

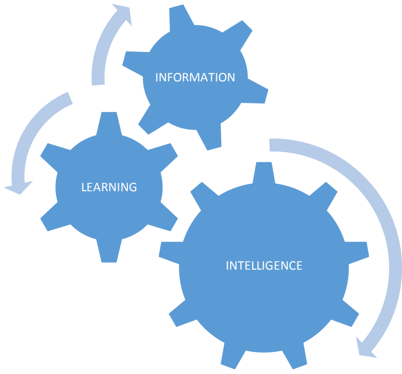

Figure 1: Gear system of learning, emergent behaviour of intelligence

C. How intelligence is achieved in machines?(RL)

According to hypothesis 2, a machine is said to be intelligent if it exhibits learning. To be more human like a machine should be able to learn in unsupervised conditions. Reinforcement learning algorithms are best suited. Generally any algorithm which adapts to a new situation and takes the decision with a goal to achieve maximum rewards is called as reinforcement learning algorithm.

A general reinforcement learning algorithm is used in a situation where data is not provided, instead generated, mathematically RL by

$$Q(s,a) = \sum_{s'} P(s,s')[R_a(s,s') + \gamma V(s')] \quad .. \tag{1}$$

s' – outcomes.
s -- State
a -- action

D. Why RL is not sufficient?

The biggest limitation of Reinforcement Learning is the curse of dimensionality [3].The algorithm doesn't consider cognitive components and lack emotional entities.

E. What is CCNS approach?

BDI (cognition) MODEL is very good for emotions but lack learning.It would be more near to human if we implement Reinforcement learning algorithm based on BDI model.

Hypothesis-4 computational cognitive neuroscience based reinforcement learning will be more human like.

Proposed Cognitive Modelling

A. Attention and perception modelling

Based on the foreground content judgment is taken. The judgment can be correct or wrong like when you are seeing somebody feeding stray dog you might think that what he /she is doing is a novel job (correct) .We find a number of factors that can be part of cognition and which influences the perception process. We can also find that perceived information can be effective or ineffective information. At this point we propose that Perception is of two types

1) Effective 2) Trivial

Perception = effective perception + trivial perception.

1. Effective perception can be represented as = perception + Attention
2. Trivial Perception = perception + no attention.

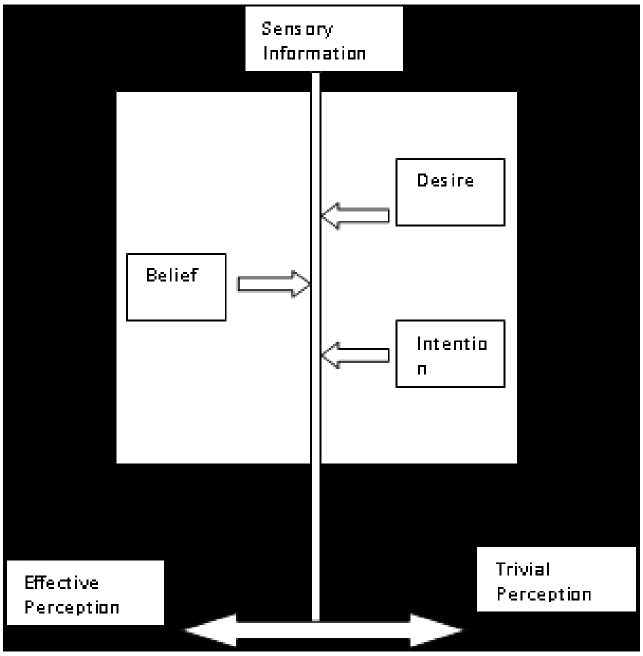

Figure 2: Trivial and effective Perception

B. Learning and memory Modelling

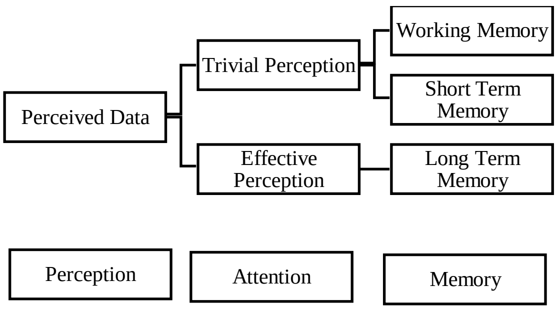

Figure 3: Attention and Memory Modelling

C. Mathematical Modelling

The Naïve Bayes classifier is simple probabilistic classifier technique based on Bayesian Theorem [6]. It is best suited when dimensionality of inputs is high. Naïve Bayes is better than sophisticated classification methods.

Consider a mixture of triangles and circles. Let triangle be our interested shape i.e. Triangle will be our effective Perception and circle would be our Trivial Perception. Our task is to identify new cases as they arrive. We have to decide the new arriving shape is of interest or not based on current available data.

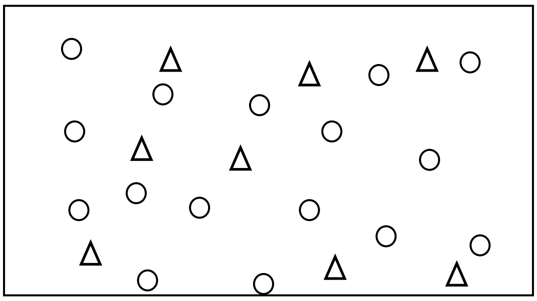

Figure 4: Combination of Circles and Triangles

Since there are twice number of circles, probability of new arrival being circle is more.

$$Probability\ of\ arrival\ of\ Circle = \frac{Number\ of\ Circle}{total\ number\ of\ Objects} \tag{2}$$

$$Probability\ of\ arrival\ of\ triangle = \frac{Number\ of\ Ttriangle}{total\ number\ of\ Objects} \tag{3}$$

The Threshold is set between the probability of circle and that of Triangle. Circle probability is 16/24, whereas triangle probability is 8/24. If we set the Threshold as 12/24, then whenever the threshold is less than 12/24, that means the new arrival is Triangle and perception has to be effective, now we will increase our attention.

Setting the Threshold using a BDI table is as shown below in Table III.

If the machine is unable to make out the perceived information then Threshold is given much Importance. For just above threshold condition the information is stored in Short term Memory.

Modified Reinforcement Learning

To tell a machine is Intelligent, we don’t have any touchstone experiment. From the beginning of computing every new feature which demonstrated Autonomy was saidto be intelligent. Later when machines were able to have computational excellence, controlling its environment, have communication between different or other computing devices were called as intelligent machines. When there features became compulsory and every machine started to have these options, those systems are known as smart devices.

We can conclude that if any device ‘A’ which exhibits autonomy, senses its environment, reacts to the changes, and take best decisions is called an Intelligent machine, whenever a new device ‘B’ with some more new intelligent feature is available then it is called as Intelligent machine and the device A is a smart device now. Hence evolution of devices bring new intelligent machines whereas previous machines are called as smarter. We can also define intelligent machine as one which exhibits Cognition, just like humans viz. extracting chunks of data, schema acquisition, building knowledge base and taking appropriate and best possible decisions in real time scenarios.

Algorithm for the abstract language PROLOG for the modelling of Attention and Perception. Prolog is a language which helps us to make sense from chunks of information, and exhibit self-learning.

Below is an algorithm which shows the modelling of Attention and Memory for Prolog.

Gathering the Data from environment
Start (input perceived data)

Check for Belief
Compare with prior threshold and likelihood for belief.
If Belief >> prior Threshold
Attention → High,
Else
Compare with prior threshold and likelihood for desire.
If Desire >> prior Threshold
Attention → High,
Else
Compare prior threshold and likelihood for Intention.
If Intention >> prior Threshold
Attention → High,
Else
Compare with prior threshold and likelihood for belief and Desire and Intention.
If BDI > prior Threshold
Attention → Medium,
Else
Attention → Low

Table 3: BDI Modelling of Attention and Memory

Type of Perception	**Parameters Deciding Perception**				
	Belief	***Desire***	***Intention***	***Level of Attention/ level of Threshold***	***Duration of storage in memory***
Effective	Yes	Yes	Yes	High	Long term memory
Trivial	No	No	No	Low	Short term/ working memory
Effective	High	X	X	High	Long term memory
Effective	X	High	X	High	Long term memory
Effective	X	X	High	High	Long term memory
Less Effective	Medium	Medium	X	Medium	Short term
Less Effective	Medium	X	Medium	Medium	Short term
Less Effective	X	Medium	Medium	Medium	Short term
Trivial	Low	Low	low	Low	working memory

Conclusions

In this paper we have given a critical review of different streams arising because of Cognitive sciences, computational Intelligence, Neuroscience and Neuromorphic Engineering. There is a new field of science which combines psychology, computer science, mathematics and neuroscience and Electronic Hardware Design. The cognitive neuroscience computing is at a verge to give rise for many potential mainstream applications. Neuromorphic engineering is one such example.

In cognitive sciences we have modeled Attention and Perception based on BDI modeling. Intelligence for ICs has been defined in a generalized way. Finally, an exciting, but very difficult, prospect is that of an integrated cognitive system which evolves; a system which absorbs new knowledge, learn through experience and respond like one of us. (Being able to combine different behaviors of humans, showing creativity).

Future work includes implementation of modified reinforcement learning of Neuromorphic VLSI chips on FPGA.

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